Explanation Augmented Feedback in Human-in-the-Loop Reinforcement Learning

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Binary Evaluations predominantly used in conventional HRL setting is not enough.

Humans explanations along with Binary feedbacks can provide significant performance gains.

We can further augment Human explanations by perturbing irrelevant regions.

Aim is to improve Feedback and Environment Sample efficiency.

QUICK FACTS

> **Integrate** Human Explanation with Binary Evaluations for Human in the loop RL

> **Explanation Augmented Feedback (EXPAND)** outperforms HRL baseline

> **25% improvement** in both Feedback Sample efficiency and Environment Sample efficiency

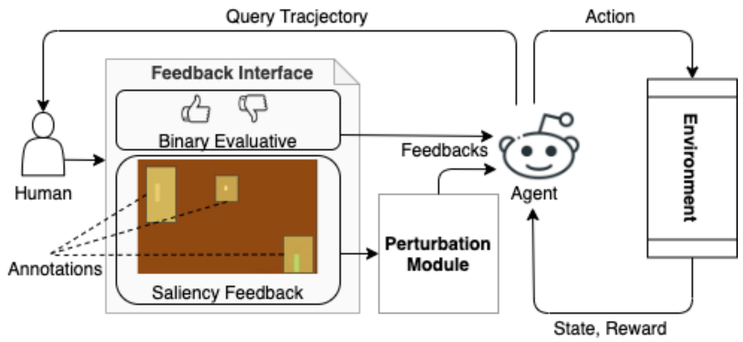
> **Focusing on relevant regions helps.**

> Results confirm that agent is indeed focusing on relevant regions.

> Employing multiple perturbations is helpful

> **Advantage Loss** on Binary Evaluations

> **Policy & Value Invariant losses** on Human Explanations



BINARY FEEDBACK & EXPLANTIONS

We learn from both Environment Reward & Human Feedback.

We use Environment Reward in conventional sense for training Off-Policy RL algorithm like DQN & obtain the L_{DQN} loss.

Using the Binary Evaluations Only :
We propose an *Advantage Loss* = L_A. It is agent's judgement on optimality of an action.

$$L_A(s,a,h) = L_A^{Good}(s,a,h) + L_A^{Bad}(s,a,h)$$

$$L_A^{Good}(s,a,h;b^h=1) = \begin{cases} 0 & ; A_{s,a} = 0 \\ Q^\pi(s,\pi(s)) - Q^\pi(s,a) & ; \text{otherwise} \end{cases}$$

Where,

$$A^\pi(s,a) = Q^\pi(s,a) - V^\pi(s) = Q^\pi(s,a) - Q^\pi(s,\pi(s))$$

$$L_A^{Bad}(s,a,h;b^h=-1) = \begin{cases} 0 & ; A_{s,a} < 0 \\ Q^\pi(s,a) - (\max_{a' \neq a} Q^\pi(s,a') - l_m) & ; A_{s,a} = 0 \end{cases}$$

Human Explanation (Saliency Information)

Policy Invariant Loss :
Under perturbations
"good" Action is always good
"bad" Action is always bad.

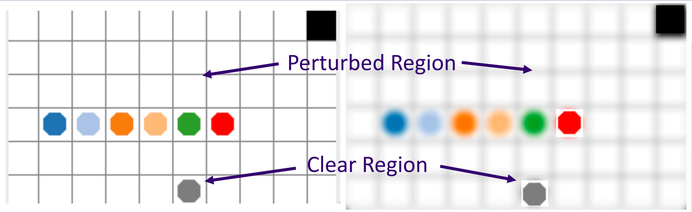
$$L_P = \frac{1}{g}(\sum_g L_A(\tilde{s}^{rg}, a, h))$$

Value Invariant Loss :
Q-values of the original state should be similar to the Q-values Perturbed states

$$L_V = \frac{1}{g}\sum_{i=1}^{g}\frac{1}{|\mathcal{A}|}\sum_{a\in\mathcal{A}}(Q^\pi(s,a) - Q^\pi(\tilde{s}^{ri},a))$$

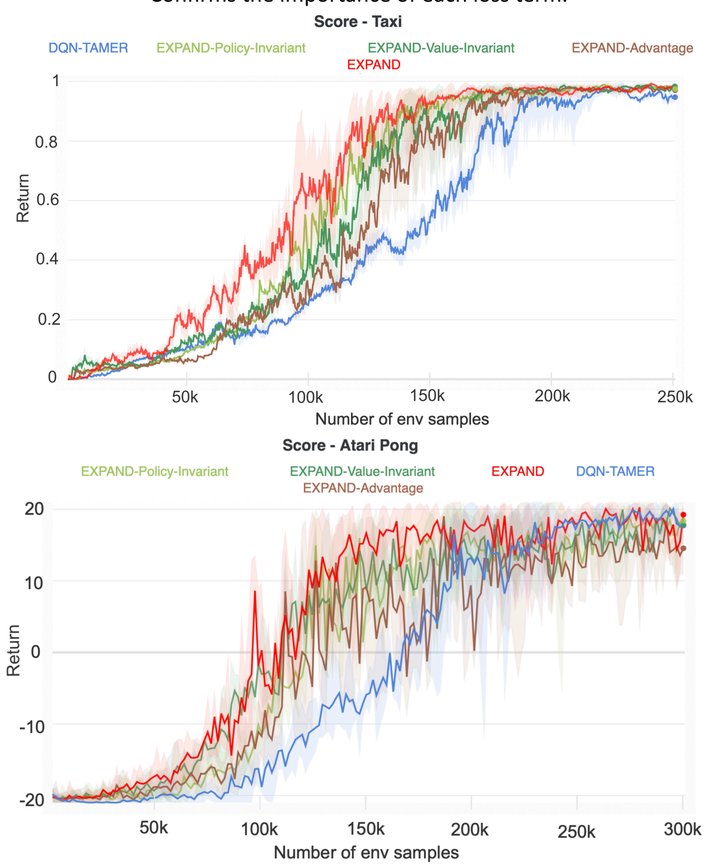
Perturbing Irrelevant State Information

We apply Gaussian Perturbations over marked irrelevant regions
In hope that such changes should not affect agent's decision making.



RESULTS

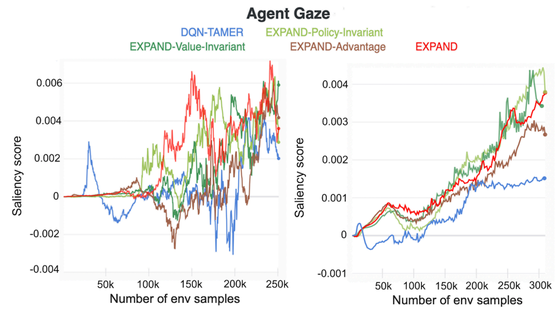
> **Domains :** Taxi & Atari-Pong
> **Metrics :**
Score : Able to reach optimal score w.r.t HRL baseline
Environment Sample efficiency : 25% improvement
Human Feedback Sample Efficiency : 25% improvement
> **Ablation :** Confirms use of binary evaluation not enough.
Confirms the importance of each loss term.



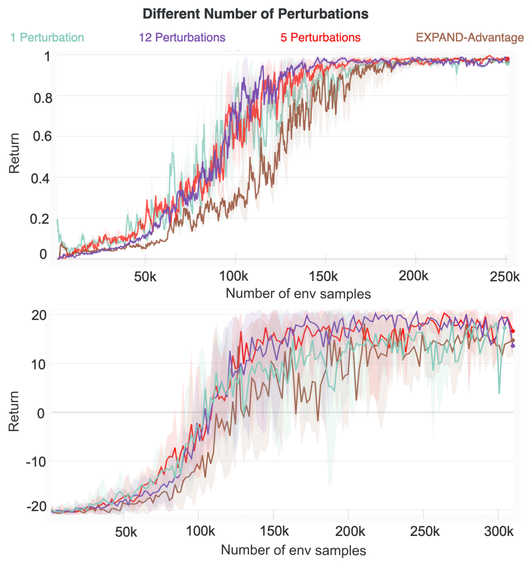
AGENT-GAZE & PERTURBATIONS

We verified our intuition :
Focusing attention towards "relevant" state regions improves performance.

$$S_F = \frac{1}{|\mathcal{A}_g|}\sum_{s_g^r \in S_g^r, a_g \in \mathcal{A}_g} SARFA(s_g^r, a_g) - \frac{1}{|\mathcal{A}_b|}\sum_{s_b^r \in S_b^r, a_b \in \mathcal{A}_b} SARFA(s_b^r, a_b)$$



We tested for the best perturbation setting :
Whether changing the number of perturbations improve agent performance.



*Equal Contribution
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